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Structural Econometric Modelling and Time Series Analysis - Towards an Integrated Approach

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Comments welcome

Abstract

In this paper we present the different approaches to modelling dynamic regression and structural equations.
First, we give a survey of the traditional econometric and the time series approaches to specification analysis of dynamic econometric models. Then, we describe the three testing procedures that are presently available to the econometrician: (1) testing for misspecification or diagnostic checking, (2) specification analysis or interpretive search, and (3) checking the overall consistency of the model.
Next, we outline the integrated structural econometric modelling and time series analysis (SEMTSA) approach to modelling dynamic linear econometric equations and point out how each of the three testing procedures can be used.
We distinguish between an analysis under full information and one under limited information.
Through the presentation of econometric modelling and time series analysis as an integrated approach, we hope to promote its development and application in empirical econometrics.

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Structural Econometric Modelling and Time Series Analysis-Towards an Integrated Approach

1. Introduction

An important and difficult part of econometric modelling is the specification of the model. Any applied econometrician knows how troublesome it can be to obtain a satisfactory specification of the model.

While the problem of specification analysis has received increasing attention in econometric research in recent years, many of the existing econometric textbooks provide few guidelines on how to obtain a satisfactory specification. This is surprising as the specification of the model is necessary in order to justify the choice of an estimation or testing procedure among the large variety of existing procedures, the properties of which are well established given that the true model is known.

The consequences of misspecification errors due to the exclusion of relevant explanatory variables are more extensively discussed in standard textbooks on econometrics. Misspecification tests such as e.g. the Durbin-Watson test belong to the tools of any empirical econometrician.

Among the exceptions to what has been said about the treatment of specification analysis in textbooks, Draper and Smith(1966) devote chapter 5 to "Selecting the 'Best' Regression Equation". Theil (1971) discusses the topic "Regression Strategies" under the heading "Frontiers of Econometrics" . Ramsey (1974) discusses "Classical Model Selection through Specification Error Tests". In his outstanding book, Leamer (1978) distinguishes six types of specification searches and presents solutions for each of them within a Bayesian framework.

But the present state of econometric modelling leads us to stress once more Zellner's(1979a) conclusion concerning the research on structural econometric models (SEM's):

"Most serious is the need for formal, sequential statistical procedures for constructing SEM's"(p.640).

In this paper, we shall outline the problems related to dynamic econometric specifications analysis and present recent contributions to the field of dynamic econometric modelling in the form of an integrated approach. Thereby, we hope to promote the application of specification analysis in empirical modelling. We shall be concerned with what Leamer calls hypothesis-testing search, interpretive search, data-selection search and postdata model construction. The hypothesis-testing search or model selection consists in choosing one element out of a set of vectors of explanatory variables. In the interpretative search, one looks for interpretable restrictions on a set of regression or structural coefficients. The issue in the data- selection search is to find the data set which is explained by a given relationship. Does the relationship fit the entire sample of observations or should the model allow for a structural change? Finally, the postdata model construction is synonymous with misspecification analysis.

In the sequel, we shall first give a survey of existing approaches to specification analysis or modelbuilding.

A distinction will be made between (1) the traditional approach to modelling regression and structural equations,(2) the time series approach to modelling dynamic regression equations and (3) the structural econometric modelling and time analysis (SEMTSA, see Zellner (1979a)), which integrate the use of econometric and time series techniques to analyse regression and structural equations in a framework of sequential testing of hypotheses.

Section 2 will be devoted to the traditional approach to modelling structural and regression equations. In section 3, we shall present the main features of the contributions of time series analysts to modelling regression equations. In section 4, different testing procedures used in the SEMTSA approach will be discussed.

A detailed presentation of the SEMTSA approach will be given in section 5.1 for the regression model and in section 5.2 for structural equations. In section 6 of this paper, we shall draw some tentative conclusions and point to problems that remain to be solved.

The estimation and testing procedures used throughout this paper are chosen on the basis of their large sample properties. Their finite sample properties are known for special models only.

Finally, notice that we shall not discuss the specification analysis - better known as "model identification"- of univariate autoregressive-integrated- moving average (ARIMA) models. This topic has been extensively treated in several textbooks (see e.g. Box and Jenkins (1970)).

2. The traditional approach to econometric modelling

The methodology of traditional econometric modelling will be briefly outlined in this section. For a more detailed description and a schematic representation of modelbuilding activities, the reader is referred to Hamilton and al.(1969) and to Zellner(1979 a).

After a statement of objectives of the study and preparatory work, viz. review of the literature, preliminary data analysis..., the investigator specifies an initial model, thereby making use of economic theory, knowledge about institutional arrangements and other subject matter considerations. Sometimes a heavily - perhaps too much - restricted model, such as e.g. a Koyck (1954) distributed lag model, is chosen as an initial model because the estimation of its parameters is straightforward.

In general, the initial model is estimated using an estimation technique which is appropriate according to criteria such as unbiasedness, consistency, efficiency...., provided the initial model is the true model. The estimation results of the model are judged on the basis of the t-values, the plausibility of the parameter estimates and their expected sign, the stability over time of the estimates, the serial correlation properties of the residuals tested by e.g. the Durbin-Watson test, and the fit of the equation measured for instance by the R^2.

When the initial model is not satisfactory as judged by one or more of these criteria, it is respecified and reestimated. For example, a significant Durbin-Watson test statistic has often led to fitting a regression model with first order autoregressive disturbances. Similarly, insignificant coefficient estimates are used as evidence in favour of excluding the corresponding variable from the equation. The finding that two-stage least squares estimates differ slightly from ordinary least squares estimates is used as argument to ignore the simultaneity aspect. Certainly, in many situations the correct remedy has been applied to cure the model. However as in medicine, different diseases may show the same symptom. It is only after a profound analysis of several symptoms, that one can be confident about the diagnosis and the prescription needed to restore the health of the patient. Similarly, as long as there is no systematic way to analyse the sample evidence, the diagnostic checking and the reformulation of the initial model may be done quite differently by two independent investigators. That different final model specifications have been reported in the economic literature for similar data sets and observation periods is evidence for this statement.

The traditional approach to modelling has certainly yielded very valuable results. These lines should not be interpreted as convicting econometricians of bad practice. Instead, we want to emphasize the need for a systematic, formal approach to econometric modelling.

3. Time series analysis of the dynamic regression model.

During the last decade , several contributions to formal modelling of regression equations have been made by time series analysts. After the presentation of their approach to modelling univariate ARIMA-models, Box and Jenkins (1970) - hereafter denoted as BJ - develop in chapters 10 and 11 of their influential book a specification procedure for dynamic regression models, also called transfer function models. As for univariate ARIMA-models, their modelling procedure for regression equations consists of three stages: identification, estimation and diagnostic checking. BJ limit themselves to the dynamic regression model with one exogenous variable. In order to outline their approach we write down the following infinite distributed lag model:

$$y_t = \sum_{j=0}^{\infty} v_j x_{t-j} + u_t \tag{3.1a}$$

or alternatively

$$y_t = v(L)x_t + u_t \, , \tag{3.1b}$$

where y_t is an endogenous variable, x_t is an exogenous variable and u_t is a normally distributed error term generated by a stationary process with mean zero and variance σ^2. One can introduce additional restrictions on the form of the error process, by assuming for example that u_t follows an ARMA-process. At the moment, we do without this additional assumption. We assume that the variable x_t is strictly exogenous, that is x_t and $u_{t'}$ are independently distributed for all t and t'. Sometimes the assumption of strict exogeneity is too strong, but it is useful in several occasions, in particular when the original model has to be transformed. In order to get a finite number of parameters, additional restrictions have to be imposed on the parameters of the model (3.1). We assume that v(L) is a rational polynomial in the lag operator L

$$v(L) = \frac{\omega_s(L)}{\delta_r(L)} L^b \, , \tag{3.2}$$

where $\omega_s(L)$ and $\delta_r(L)$ are finite polynomials in L of degree s and r respectively

$$\omega_s(L) = \omega_0 - \omega_1 L - \ \dots \ -\omega_s L^s , \tag{3.3a}$$

$$\delta_r(L) = \delta_0 - \delta_1 L - \ \dots \ -\delta_r L^r$$

with $\delta_0=1$. b allows for some "dead" time in the response pattern of y_t to x_t . Under the assumption(3.2), the model(3.1) is Jorgenson's (1966) rational distributed lag model. We can rewrite (3.2) as

$$\delta_r(L)v(L) = \omega_s(L)L^b \ . \tag{3.4}$$

This implies the following restrictions on the v_j's

$$v_j = 0 \ , \ j = 0,1, \dots ,b-1 \tag{3.5}$$

$$v_j = \delta_1 v_{j-1} + \delta_2 v_{j-2} + \dots + \delta_r v_{j-r} + \omega_0 \ , \ j = b$$

$$v_j = \delta_1 v_{j-1} + \delta_2 v_{j-2} + \dots + \delta_r v_{j-r} - \omega_{j-b} \ , \quad j = b+1, \dots b+s$$

$$v_j = \delta_1 v_{j-1} + \delta_2 v_{j-2} + \dots + \delta_r v_{j-r} \ , \qquad j > b+s \ ,$$

so that for $j \geq b+s-r$, the v_j's follow an r^{th} order difference equation. The specification or identification of the model consists in the determination of the values of b, s and r from the pattern of the estimated v_j's . Often the infinite process (3.1) can be well approximated by an finite distributed lag model of order k , that is $v(L) \simeq \sum_{i=0}^{k} v_i L^i$. Solving the Yule-Walker equations for a k^{th} order approximation, we obtain

$$E\, y_t\, x_{t-\tau} \simeq v_0\, E\, x_t\, x_{t-\tau} + v_1\, E\, x_{t-1} x_{t-\tau} + \dots + \\ + v_k\, E\, x_{t-k}\, x_{t-\tau} \tag{3.6}$$

$$\tau = 0, 1, 2, \dots k \ .$$

Rough estimates of the v_j's can be obtained by replacing the expectations in (3.6) by corresponding sample moments and solving for the v_j's . This is equivalent to regressing y_t on current and lagged values of x_t . If the x_t's are orthogonal, the v_j's can be estimated in a straight-forward way. BJ assume that the input varable x_t is generated by an autoregressive - integrated - moving average (ARIMA) model

$$\varphi_x (L) \Delta^{d_x} x_t = \theta_x (L) \varepsilon_{xt} \quad , \tag{3.7}$$

where $\varphi_x (L)$ and $\theta_x (L)$ are finite degree polynomials in x , Δ is the difference operator, d_x is some positive integer and ε_{xt} is a white noise disturbance term with variance σ_x^2 . Premultiplying equation (3.1) by $\theta_x^{-1}(L)\varphi_x (L) \Delta^{d_x}$ and substituting (3.7) yields

$$\theta_x^{-1}(L)\varphi_x (L) \Delta^{d_x} y_t = v (L) \varepsilon_{xt} + \theta_x^{-1}(L) \varphi_x (L) \Delta^{d_x} u_t \tag{3.8}$$

or

$$w_t = v(L) \varepsilon_{xt} + \eta_t \tag{3.9}$$

with

$$w_t = \theta_x^{-1}(L) \varphi_x (L) \Delta^{d_x} y_t \quad \text{and} \quad \eta_t = \theta_x^{-1}(L) \varphi_x (L) \Delta^{d_x} u_t \quad .$$

If the parameters of the ARIMA model for x_t are known, we can compute the ε_{xt}'s and use the Yule-Walker equations for model (3.9)

$$E (w_t \varepsilon_{xt-j}) = v_j \sigma_x^2 \quad , \tag{3.10}$$

where the unknown expectations have to be replaced by their sample moments, to estimate the v_j's. From (3.10), it is obvious that the v_j's are proportional to the correlations between w_t and ε_{xt-j} , so that we can determine the values of b, s and r from the estimated correlations between w_t and ε_{xt-j} .

Using Bartlett's (1946) formula for the covariances of sample correlation coefficients, BJ show that under the assumption that y_t and $x_{t'}$ are uncorrelated for all t and t' (all v_j's are zero), the covariance between estimated correlation coefficients is approximately equal to

$$\text{cov} [r_{w\varepsilon_x}(k) , r_{w\varepsilon_x}(k+l)] \simeq (n-k)^{-1} \rho_{ww} (l) \quad , \tag{3.11}$$

where $r_{w\varepsilon_x}(k)$ is the k^{th} order sample correlation coefficient between w_t and ε_{xt} , n is the sample size and $\rho_{ww}(l)$ is the l^{th} population autocorrelation coefficient for w_t .

The result in (3.11) also holds true approximately in large samples if the parameters of the process for x_t are unknown but can be estimated consistently. The covariance in (3.11) is proportional to the autocorrelation function of w_t , so that if w_t is a white noise, the covariances in (3.11) are zero for $l \neq 0$.

This last remark is used by Granger and Newbold (1977) among others as an argument in favour of filtering also the variable y_t into a white noise process ε_{yt} given by

$$\varphi_y (L) \Delta^{d_y} y_t = \theta_y (L) \varepsilon_{yt} \tag{3.12}$$

and then analyzing the cross-correlation function between ε_{yt} and ε_{xt}. This correlation function exhibits the same pattern as the polynomial $v^* (L) = \theta_y^{-1} (L) \varphi_y (L) \Delta^{d_y - d_x} v(L) \theta_x (L) \varphi_x^{-1} (L)$ in

$$\varepsilon_{yt} = v^* (L) \varepsilon_{xt} + \eta_t^* \tag{3.13}$$

with $\eta_t^* = \theta_y^{-1} (L) \varphi_y (L) \Delta^{d_y} u_t$.

At this point, we like to make several comments on the identification of transfer functions as proposed by BJ and refined in more recent contributions.

1) Usually the approach is applied to regression equations with one explanatory variable x_t . Although one can generalize it for models with more than one explanatory variables, it will become extremely difficult - if not possible - to determine with some accuracy the values of b, s and r for models with several exogenous variables. On the other hand, as most data in econometrics are non-experimental, one has to take into account the effects of the explanatory variables, which vary over the sample period. Therefore, there will usually be more than one explanatory variable included in econometric regression equations, so that the time series approach to modelling transfer function equations will hardly be applicable to them.

2) The assumption that the exogenous variable is generated by an ARIMA process may be unrealistic. The typical situation in econometrics is that of a structural change during the observation period. Many of the structural changes can be modelled by expanding the set of explanatory variables, using dummy variables or products of explanatory variables and dummy variables. A structural change in the parameters of the ARIMA model for x_t only does not hamper the analysis of the regression function of y_t on x_t as long as the marginal process for x_t is of no direct interest in the analysis. Nevertheless, if one wants to transform the process of x_t into a white noise, the presence of a structural change in the process of x_t will complicate matters substantially.

3) Usually when the model is described by (3.1) with the additional assumption that the variable x_t is generated by (3.7), the form and the parameter values of the linear filters in (3.7) are not known. The degree of the two polynomials in (3.7) has to be determined and the parameters have to be estimated.

Substituting estimates for the parameters in $\varphi_x(L)$ and $\theta_x(L)$ may crucially affect the shape of the estimated v_j's - especially, when the number of observations is not too large as is often the case in econometrics. In addition, applying the filters as in (3.8), whether they are known a priori or estimated, removes the multicollinearity at the price of introducing or adding autocorrelation in the disturbances u_t of the regression equation.

4) In tests on the cross-correlations of prewhitened series, the favourite null hypothesis is usually that of independence between the series. Under this hypothesis, the population correlation coefficients of the prewhitened series are zero and the asymptotic distribution of the sample cross correlation is known. They are independently normally distributed with mean zero and variance equal $(n-k)^{-1}$ (see formula (3.11)).

An asymptotic test of the null hypothesis of independent series is easily constructed. However, in econometric applications, where economic theory indicates that there is a relationship between endogenous and exogenous variables, the hypothesis of independence of the series is not the most natural null hypothesis. Rather, econometricians often would like to find out what the shape of the lag distribution between y_t and x_t looks like, given that there exists a relationship between the series.
All this is not to say that the approach proposed by BJ (1970), refined and extended by other time series analysts in the last decade is not useful in a regression equation context. Their approach seems to be inappropriate in many econometric applications, but it can be very valuable when the aim of an application is to forecast an economic series using a leading indicator in order to increase the forecasting precision. It is also in a forecasting context that concepts such as Wiener-Granger causality (see e.g. Granger (1969)) have been presented and that they should be placed. The use of the word "causality" in this context is misleading (see e.g. Zellner (1979b) on this point). When the bivariate model constitutes the appropriate framework of analysis, the absence of Wiener-Granger causality in one or both directions yields useful testable restrictions on the parameters of the process. It implies that the cross correlation function between the prewhitened series is one-sided for unidirectional causality or that the cross correlations are zero for all leads and lags (except zero) in case of absence of Wiener-Granger causality in both directions.
A methodology for first testing that there is unidirectional causality from x to y only (absence of feedback) and then modelling the dynamic regression equation is given by Haugh an Box (1977). Two examples of economic time series illustrate their procedure.

These restrictions are useful for the purpose of forecasting and control. They can be tested and, when they are not rejected, they can be imposed on the parameters. The final test however consists in checking the out-of-sample forecasting and/or control performance (see e.g. Ashley et al. (1980), Neftçi (1979)).
For the purpose of forecasting and control, the null hypothesis of absence of Wiener-Granger causality in one or both directions is very relevant. For instance, non-rejection of the null hypothesis that x_t does not "cause" y_t is an indication that the use of x_t as a leading indicator to forecast y_t will not be very effective.

From the discussion in this section, we conclude that the time series approach to modelling a dynamic regression equation is not always appropriate for the econometric applications. In applied work, one has to combine it with existing econometric techniques. Before presenting an integrated approach which is a blend of econometric and time series methods, we shall outline different testing procedures in the next section.

4. Testing procedures

Recent research on testing procedures for dynamic econometric modelling can be classified in three categories, namely analysis of misspecification, of specification and of the overall consistency of the model. The term misspecification analysis is synonymous with diagnostic checking. After a model has been specified and estimated, one checks whether the assumptions underlying it are indeed satisfied.

Examples of misspecification tests are the Durbin-Watson test and Durbin's h-test for first order autocorrelation in the disturbances of the linear regression model without and with lagged endogenous variables present. Misspecification analysis means that, given a model, one investigates whether more general models are more appropriate according to some criterion. It is going from specific to general, to use the terminology of Mizon and Hendry (1980) [see also Mizon (1977)]. Misspecification analysis is an explicit part of the BJ-approach, where it is called diagnostic checking. In recent years, many research efforts have been devoted to finding misspecification tests. Silvey's (1959) Lagrange multiplier and Rao's (1973) efficient score testing principle are well suited for misspecification analysis and many of the recently developed tests are applications of these principles (see e.g. Godfrey (1978a,b), Breusch and Pagan (1980)). Finally, it should be noticed that misspecification analysis is and has to be part of thorough econometric modelling.

Specification analysis goes the opposite direction, that is one starts with a general model and tests the restrictions on the parameters of the general model. If the restrictions are not rejected by the data, they have to be imposed on the parameters. Then, additional restrictions are considered in the framework of the restricted model.

Testing is done within the framework of a given model. Examples of specification tests are the F-test of linear restrictions on a set of coefficients, the t-test on a single regression coefficient. A useful testing principle for specification analysis is the Wald (1943) principle, for which the small sample or asymptotic distribution of the restrictions under the null hypothesis is derived from the distribution of the unrestricted parameter estimates.
The two tests mentioned above are examples of Wald-type tests.

Testing procedures in the third category have been designed to check the overall consistency of the model with a priori information and with the information in the data. A first question is whether the different equations in the model fit together. Current practice is to solve the complete model either analytically, if the model is linear, or numerically, if the model is nonlinear. Implausible values for the multipliers and for the solution of the model computed analytically or determined approximately through simulation lead to a reformulation of the model.

The analysis should be extended to empirically checking the transfer function form implied by the model (if it is linear) as has been proposed and done by e.g. Zellner and Palm (1974). Computing the roots of the characteric equation will give insight into the long-run properties of the model.
If the exogenous variables in the model are generated by a vector ARMA-process, the final equations can also be checked empirically in order to validate the model. For applications, we refer to Zellner and Palm (1974, 1975) and Wallis (1977) among others.

The next section will be devoted to the SEMTSA approach to modelling regression and structural equations. Thereby, we shall point out what the role of the three testing procedures is.

5. Structural econometric modelling and time series analysis

5.1 Modelling dynamic regression equations

The reader may wonder why the modelling of regression equations is discussed under the heading SEMTSA.
The reason for this is twofold. First, we emphasize the interpretive search in modelling regression equations, viz. the use of theoretically meaningful restrictions on the regression coefficients. In recursive models and in single equation models, the structural equations are in regression equation form and can be modelled as such. Second, for the analysis of reduced and transfer function form equations, which are also regression functions, we prefer to use tested overidentifying restrictions, which have an interpretation in terms of economic behaviour to using tested restrictions, which have the only merit to be easily incorporated into the model.
Recently developed approaches to modelling a dynamic regression equation start with a specification analysis. One specifies a fairly general (linear) dynamic regression model

$$\beta_0(L)\, y_t = \sum_{i=1}^{k} \beta_i(L)\, x_{it} + u_t \quad , \tag{5.1}$$

with k explanatory variables x_{it} , u_t being a normally distributed disturbance term, which is assumed to be independent of $x_{it'}$, for all t and t' and $i = 1, 2, \ldots, k$. The $\beta_i(L)$'s , $i = 0, 1, \ldots, k$, are polynomials in the lag operator L of finite degree p_i , and $\beta_0(0) = 1$.
The meaning of 'fairly general' is that the number of explanatory variables and/of lags included is sufficient to guarantee the white noise assumption for the u_t's .
For autoregressive disturbances

$$\rho(L)\, u_t = \varepsilon_t \quad , \tag{5.2}$$

where $\rho(L)$ is a polynomial of finite degree r in L , the model (5.1) can be written exactly as a dynamic regression with finite distributed lags and white noise errors

$$\rho(L)\, \beta_0(L)\, y_t = \rho(L) \sum_{i=1}^{k} \beta_i(L)\, x_{it} + \varepsilon_t \quad , \tag{5.3}$$

which illustrates the interaction between 'explained' part and the disturbance correlation properties in a dynamic equation (see e.g. Sargan (1964)).
If the disturbances u_t are generated by a moving average process

$$u_t = \Theta(L)\, \varepsilon_t \quad , \tag{5.4}$$

where $\Theta(L)$ is a finite polynomial in L, the transformation of (5.1) through premultiplication by $\Theta^{-1}(L)$ yields infinite distributed lags for the explanatory variables. There are three solutions to this: (a) ignore the autocorrelation in the disturbances, (b) approximate the infinite distributed lags by finite ones, and (c) use the exact model (5.1) under (5.4), thereby modelling the correlation structure of the disturbances explicitly. If the solution (a) is adapted, one can estimate the regression coefficients by ordinary least squares if $\beta_0(L) = 1$, or use an instrumental variable estimation method, if there are lagged values of y_t present in (5.1). None of these methods will be asymptotically efficient. Also the usual test statistics for exclusion and other linear restrictions on the parameters have to be reformulated to take into account the autocorrelation in the disturbances. This point will be taken up below.

In order to limit the size of the approximation error under solution (b), the number of lags included in the regression will usually have to be large, so that ignoring the restrictions implied by the moving average error process can lead to a substantial loss of degrees of freedom. Finally, although modelling the moving average process for the disturbances jointly with the regression coefficients can be computationally cumbersome, it is necessary for achieving efficient estimation. Starting the specification analysis with a general model with serially uncorrelated disturbances has the following advantages:

1) All the dynamics are incorporated in the systematic (explained) part of the equation instead of being left in the disturbance term. This enables the investigator to interpret the parameters more easily in terms of economic behaviour.

2) If the disturbances of the initial regression model are uncorrelated and homoscedastic, OLS has well-known optimal properties besides its obvious computational advantages, which can be important in a sequential testing set-up.

   In a regression model with autocorrelated disturbances but no lagged endogenous variables present, the OLS-estimator is unbiased and consistent, but it is not efficient and the formula for the standard errors for OLS is no longer appropriate. Similarly, the F- and t-tests for linear and exclusion restrictions are no longer valid as such. Indeed, Kiviet (1979) derives lower and upper bounds for the effects of ARMA disturbances on tests for regression coefficients. He shows that a 't-value' of about 2 usually falls between the lower and upper bounds, so that the test is inconclusive at least if no additional information on the model is used. For the test to be conclusive, the 't-value' has to be much higher, especially vor problems with sample size smaller than 50 .

3) Most importantly, the general initial model can be used as a maintained hypothesis throughout the specification analysis. Of course, the lag length in the initial model can formally be tested for. This problem has been studied in the literature on choosing the length of a distributed lag (see e.g. Amemiya and Morimune (1974), Mouchart and Orsi (1976) or Sargan (1980a)).

If the initial model is formulated such that the true model is nested within it, the specification analysis aims at searching for the true model inside the initial model. As long as the true model is nested in the restricted model under the null hypothesis H_0 , the distribution of the test statistics under H_0 is correct and the data can guide us towards the true model. Usually, the investigator will formulate a sequence of nested hypotheses on the parameters of the initial model and test whether more restricted versions of the model are compatible with the data. Restrictions such as that of a common factor $\rho(L)$ in (5.2) and (5.3) can be included in the sequence of restrictions. Tests of specification in the form of a uniquely ordered nested sequence have optimal statistical properties. They are uniformly most powerful (see Anderson (1971), p. 263) in the class of unbiased tests.

Although starting with a loosely parametrized model implies a loss of degrees of freedom and possibly the presence of high multicollinearity between the regressors, it reduces the danger of analysing inappropriate and too restricted models.
In agreement with Zellner and Palm (1974), rejecting the nested model when it is true, will be a less serious error than using a restricted model when the restrictions are not true. This is an argument in favour of a specification analysis starting with a general model.

Several authors advocate - for very different reasons - to start with a general model. For instance, Sims (1980) argues that we do generally not have strong a priori knowledge (restrictions) to impose on the model. Therefore, he works with models with a large number of parameters. Mizon (1977), Hendry and Mizon (1978), Davidson and al. (1978), Mizon and Hendry (1980) among others propose to start with a general model, specify a uniquely ordered sequence of nested hypotheses and compare them using formal statistical tests.
As stated above, we shall follow the same line in this paper. Economic

theory and other a priori knowledge play an important role in the choice of the explanatory variables to be included in the initial model. Next, the assumptions underlying the estimated initial model should be checked. For instance, the disturbance correlation properties can be tested in a formal way using the Pierce test (1971), when the alternative hypothesis is not explicitly specified for a regression model that does not contain lagged endogenous variables, or a Lagrange multiplier test (see Silvey (1959)), when the null hypothesis of absence of autocorrelation in the disturbances is compared to a given alternative hypothesis. Often, it is sufficient to plot the residuals and to check informally their serial correlation properties. Systematic patterns in the residuals provide evidence against the generality of the starting model and may yield useful insight on how to extend and reformulate the initial model.

A very important stage of modelling is the formulation of testable restrictions on the parameters of the initial model. A first kind of restrictions is mainly characterized by the fact that they are easily imposed on the model. Examples are the well known exclusion restrictions, the Almon (1965) polynomials, which are equivalent to linear restrictions on distributed lag coefficients, and the common factor restriction mentioned earlier. Suppose that one starts with the model

$$\beta_0^* (L)\, y_t = \sum_{i=1}^{k} \beta_i^* (L)\, x_{it} + \varepsilon_t \quad , \tag{5.5}$$

where $\beta_i^* (L)$, $i = 0, 1, 2, \ldots, k$ are unrestricted polynomials in L of finite degree $p_i + r_i$. The presence of r common factors in (5.5) implies rk restrictions on the $\beta_i^* (L)$, i.e. $\beta_i^* (L) = \rho(L)\, \beta_i(L)$, $i = 0, 1, 2, \ldots, k$, and yields model (5.1) with autoregressive errors (5.2). Dynamic regression models with autoregressive errors have been frequently used in applied econometrics. There are many estimation methods available for estimation of these models. A comprehensive presentation of the estimation methods is given by Hendry (1976).

Two problems can occur in the common factor analysis. Sometimes it is difficult to formulate the nonlinear restrictions on the parameters of the initial model implied by the presence of common factors. However, explicit expressions for these restrictions are needed in order to apply a Wald-type test. Sargan (1980b) has shown that the problem can be formulated in terms of restrictions on a determinantal equation, that can be tested in a straightforward way using the Wald principle. Of course, the problem of formulation of the restrictions could be circumvented by using a likelihood ratio test instead of a Wald-type test. Then however, one may face the problem of multiple optima of the likelihood function.

A second difficulty arises with the occurence of complex roots in the common factor polynomial $\rho(L)$. If one tests for the presence of one common factor (with a real root), while there is a pair of common factors present with complex roots, one might conclude that there are no common factors present. The solution to this problem is to test for the presence of a pair of common factors, although the null hypothesis of one common factor has been rejected (see Sargan (1977)).
Upon acceptance of the common factor hypothesis, one tests the hypothesis that the roots of the common factors are zero. This last test is similar to the Durbin-Watson test, where one tests the null hypothesis of the first order autocorrelation coefficient of the disturbances is zero.

Finally, it should be noticed that the economic interpretation of the common factor restriction is not always obvious.
Theoretically meaningful restrictions on the regression coefficients form a second kind of restrictions. Several examples can be given. They also apply to structural equations.

1) A partial adjustment model for the endogenous variable and/or expectation scheme's, such as adaptive and rational expectations, lead to restricted dynamic regression models.

2) Exclusion restrictions as the result of some causal mechanism are justified by considerations from economic theory.

3) The requirements of homogeneity of degree zero or one with respect to some or all explanatory variables yield testable restrictions on the parameters of the initial model.

4) An 'error correction' mechanism, such as introduced by Davidson ed al. (1978) and by Hendry and Mizon (1978), and by Hendry (1978) and Blommestein and Palm (1980), can be interpreted as a set of restrictions on regression or structural coefficients. Consider the following demand function for money:

$$\ln M_t = \alpha_0 + \alpha_1 \ln M_{t-1} + \alpha_2 \ln Y_t + \alpha_3 \ln Y_{t-1} + \\ + \alpha_4 \ln P_t + \alpha_5 \ln P_{t-1} + \alpha_6 \ln R_t + u_t , \qquad (5.6)$$

where M_t is the demand for nominal balances, Y_t is disporable income in constant prices, P_t is the income deflator, and R_t is an interest rate.

It can be formulated as an equation relating variables expressed in first differences, Δ , and in levels

$$\Delta \ln M_t = \alpha_0 + \alpha_2 \Delta \ln Y_t + \alpha_4 \Delta \ln P_t + (\alpha_1 - 1) \ln \left(\frac{M}{PY}\right)_{t-1} + \\ + \alpha_6 \ln R_t + u_t \quad , \qquad (5.7)$$

provided the following linear restrictions hold $\alpha_1 = -\alpha_3 = -\alpha_5$.

From equation (5.7) it is obvious that using differenced variables can be equivalent to imposing restrictions on the parameters of a dynamic model. Notice that the disturbance term u_t is not affected by the introduction of differenced variables. In (5.7), the rate of change of M depends on the liquidity - income ratio $(\frac{M}{PY})$ or the inverse of the velocity at time $t-1$, that is $\Delta \ln M_t$ is 'corrected' for $[\ln M_{t-1} - \ln (PY)_{t-1}]$. More important are the long-run properties of the non-stochastic part of (5.7).
In steady state growth with $\Delta \ln M_t = g_1$, $\Delta \ln Y_t = g_2$ and $\Delta \ln P_t = g_3$ $(g_1 = g_2 + g_3)$, the solution to (5.7) yields

$$M = A R^{\gamma} PY \quad , \qquad (5.8)$$

with $$A = \exp\left[\frac{g_1 - \alpha_0 - \alpha_2 g_2 - \alpha_4 g_3}{\alpha_1 - 1}\right] \quad , \quad \gamma = \frac{-\alpha_3}{\alpha_1 - 1} \; .$$

From (5.8) , we see that in steady state growth, the demand for money is homogeneous of degree one in income and prices. Further, the steady state velocity of money $\frac{PY}{M}$, depends on the interest rate (the parameter γ is expected to be negative). Notice that the factor A varies with the growth rates, but is constant under steady state growth.
In short, specification (5.7) has theoretically meaningful long-run properties. More details about the properties of models with 'error correction' mechanism can be found in the references cited above. Much in this line is also the 'integral correction' mechanism proposed and applied by Hendry and Von Ungern-Sternberg (1979).
Restrictions which have an interpretation in terms of economic behaviour are to be preferred to those which have the only advantage of being easily tested and imposed on the parameters.

The restrictions considered in the interpretive search should possibly be formulated as a uniquely ordered sequence of nested hypotheses in order to assure good asymptotic properties of the statistical procedure (see Anderson (1971)).

Selecting a uniquely ordered sequence will be quite difficult in practice, as several alternative sequences might be a priori reasonable. In their study on the demand for money in the Netherlands, Blommestein and Palm (1980) first tested for the presence of a common factor. The hypothesis was not rejected at conventional levels of significance. Alternatively, starting with the same initial model, they also tested the joint hypothesis of a unit steady state elasticity of nominal money balances with respect to income and prices, and a steady state velocity of money depending on the interest rate only. This alternative hypothesis was not rejected at the conventional significance levels.
The final choice between the two sequences of hypotheses had to be made on considerations other than statistical ones. The authors chose to impose theoretically plausible restrictions.

In general, when a hypothesis in the sequence is not rejected by the data, it is imposed on the model. As a safeguard against misspecification, the autocorrelation properties of the residuals and the assumption of homoscedasticity should be checked. The sequence of tests stops, when one hypothesis is rejected or when the last hypothesis cannot be rejected while the residuals of the most restricted model do not indicate any misspecification. The model finally retained is used to forecast the data outside the sample period. The forecasts are compared to the realized data provided these are available.

As a yardstick to compare the forecasting properties, one can use a univariate ARIMA model to forecast the endogenous variable. If the univariate model predicts more accurately than the dynamic regression model does, one should conclude that the latter one is misspecified. If none of the two models predicts reasonably well, there is the possibility of a structural change or of a misspecification of the regression model.
The predictive performance of the model can be formally checked using a test based on the distribution of the forecasting errors - either assuming that the parameters of the model are known (see e.g. Hendry (1978)) or that they have been estimated (see e.g. Dhrymes and al. (1972)).
Finally, if the exogenous variables can be represented by univariate (not necessarily independent) ARIMA schemes

$$\varphi_i (L) \Delta^{d_i} x_{it} = \theta_i (L) \varepsilon_{it} , \tag{5.9}$$

we can investigate the implications of the specification of the regression model for the marginal process of the endogenous variable.
Substitution of (5.9) into (5.1) yields

$$\phi_0 (L)\, y_t = \sum_{i=1}^{k} \phi_i (L)\, \theta_i (L)\, \varepsilon_{it} + v_t \quad , \tag{5.10}$$

where $\phi_0 (L) = \beta_0 (L) \prod_{j=1}^{k} \varphi_j (L)\, \Delta^{d_j}$,

$$\phi_i (L) = \beta_i (L) \prod_{\substack{j=1 \\ j \neq i}}^{k} \varphi_j (L)\, \Delta^{d_j} \quad , \qquad i = 1, 2, \ldots, k \quad ,$$

and $v_t = \prod_{j=1}^{k} \varphi_j (L)\, \Delta^{d_j} u_t$. The r.h.s. of (5.10) is a sum of $k+1$ MA processes and can be represented as a MA in one variable, say $\theta_0 (L)\, \varepsilon_{0t}$, so that (5.10) becomes

$$\phi_0 (L)\, y_t = \theta_0 (L)\, \varepsilon_{0t} \quad . \tag{5.11}$$

Expression (5.11) is the univariate ARIMA representation for y_t . Given that the univariate ARIMA models for the endogenous and exogenous variables have been determined empirically, one can check along the lines proposed by Zellner and Palm (1974) whether substitution of them into the dynamic regression model yields the univariate ARIMA model for y_t .

The approach to modelling a dynamic regression equation can be summarized as follows:

1) formulate a general initial model, use economic theory and other relevant a priori information,
2) check the assumptions underlying the initial model, e.g. error serial correlation properties, homoscedasticity, parameter stability, lag length,
3) formulate a uniquely ordered sequence of nested hypotheses, test from general to specific, stop if one null hypothesis in the sequence has to be rejected, adjust thereby the individual significance levels using e.g. the Bonferroni inequality or the Scheffé procedure (see Savin (1980)) in order to get a test with a given overall size,
4) check the assumptions underlying the most restricted model, for which the restrictions are not rejected by the data,
5) check the forecasting performance of the model to detect a possible misspecification and/or a structural change,
6) check the implications of the model for the univariate ARIMA representations.

In the next section, we shall adapt and extend the approach to modelling structural equations.

5.2 Modelling structural equations

The specification analysis of linear dynamic structural equations is more complicated than that of dynamic regression equations. Estimation and testing procedures have to take into account the presence of simultaneity and the problem of identification has to be solved. Among the restrictions, we have to distinguish between those necessary to identify the model and the overidentifying restrictions which can be tested.

Before starting with the specification analysis, one has to decide whether a full information analysis of the complete initial model is feasible and desirable or whether one has to opt for an analysis under limited information (not necessarily through limited information maximum likelihood). Due to the size of the simultaneous equation models used in practice, a full information analysis will hardly be feasible in most instances - except perhaps for models constructed for a small scale purpose. In addition, one might expect an analysis under limited information to be robust against errors of misspecification in the remaining equations. With respect to the single equation methods applied to a simultaneous equation model with autoregressive errors, Hendry (1974) concludes that they pointed up the existence of misspecifications and provided clues to its solution (p. 576). About the disadvantages of testing subgroups of larger hypotheses, as will happen with a specification analysis under limited information, Darroch and Silvey (1963) write (p. 557): "Separate tests of h_1 and h_2 may induce a poor test of $h_1 \cap h_2$ because it is possible that for some Θ with high probability, $L(h_1)$ and $L(h_2)$ are both 'near 1' while $L(h_1 \cap h_2)$ is small". For this reason, Byron (1974) suggests to test the restrictions on single structural equations first and, on the acceptance of all these tests, to test jointly for all overidentifying restrictions on the reduced form.

The computational intractability of an analysis under full information due to the size of the model has been put forward by Drèze (1976) as an argument in favour of limited information analysis in a Bayesian context. More recently, Malinvaud (1980) stressed this argument in a call for more research into estimation and testing procedures under limited information. An example of formal specification analysis of a system of structural equations has been provided by Hendry and Anderson (1977) for a model of the Building Society in the United Kingdom.

In order to outline their approach, we consider the following dynamic simultaneous equation model

$$\underset{m\times m}{H_{11}(L)}\ \underset{m\times 1}{y_t} + \underset{m\times k}{H_{12}(L)}\ \underset{k\times 1}{x_t} = \underset{m\times 1}{u_{1t}} \quad , \tag{5.12}$$

where y_t and x_t are vectors of endogenous and exogenous variables, u_{1t} is a vector of disturbances, $H_{11}(L) = \sum_{i=0}^{r} H_{11i} L^i$ and $H_{12}(L) = \sum_{i=0}^{p} H_{12i} L^i$ are matrices, whose elements are finite polynomials in the lag operator of degree r and p resp. .
The matrix $H_{11}(L)$ has full rank. Further, we assume that the disturbances are normally independently distributed with mean zero and covariance matrix Σ_{11} . We assume strong exogeneity, that is, x_t and $u_{1t'}$ are independent for all t and t' . Although strong exogeneity is often not a necessary condition, it has the advantage to preserve the independence of the x_t's and the disturbances under linear transformations such as that involved in the derivation of the final form of a model.

Notice that the disturbances are assumed to be uncorrelated. In order to incorporate all the dynamics into the model, sufficiently long lags are included in the systematic part.
Hendry and Anderson (1977) first test for the presence of common factors in the unrestricted reduced form

$$y_t = \pi_0(L)\, y_t + \pi_1(L)\, x_t + v_t \quad , \tag{5.13}$$

where $\pi_0(L) = - H_{110}^{-1} \sum_{i=1}^{r} H_{11i} L^i = \pi_{01}L + \pi_{02}L^2 + \ldots + \pi_{0r}L^r$,

$$\pi_1(L) = H_{110}^{-1} \sum_{i=1}^{p} H_{12i} L^i = \pi_{10} + \pi_{11}L + \ldots + \pi_{1p}L^p \quad , \quad v_t = H_{110}^{-1}u_{1t} \ .$$

Imposing e.g. one common factor (I-RL) restriction leads to

$$y_t = \sum_{i=1}^{r-1} P_{0i}\, y_{t-i} + \sum_{i=0}^{p-1} P_{1i}\, x_{t-i} + (I-RL)^{-1}\, v_t \quad , \tag{5.14}$$

where $P_{01} = \pi_{01}$, $P_{0i} - RP_{0i-1} = \pi_{0i}$, $i = 2, \ldots, r-1$, $-RP_{0r-1} = \pi_{0r}$

and $P_{10} = \pi_{10}$, $P_{1i} - RP_{1i-1} = \pi_{1i}$, $i = 1, \ldots, p-1$, $-RP_{1p-1} = \pi_{1p}$.

If the common factor restrictions are not rejected, one proceeds to test the joint hypothesis that all the autoregressive parameters are zero, and upon acceptance of the joint hypothesis $R = 0$, these restrictions can be imposed on the model (5.14). Otherwise, one ought to use the model (5.14) with first order vector-autoregressive error. In both cases, the next step consists in formulating and testing a set of say n overidentifying restrictions on the reduced form parameters. If the overidentifying restrictions are rejected, the identifying restrictions on the parameters may require modification too.

Sims (1980) also puts forward a systems approach to macroeconomic modelling. First, he argues that most of the macroeconomic models are not overidentified in contrast to what is commonly assumed. For this reason, he starts with an unrestricted vector autoregressive model in which no distinction is made between endogenous and exogenous variables. The number of lags included is restricted to be finite. His model can be written as

$$\underset{(m+k)\times(m+k)}{H(L)} \quad \underset{(m+k)\times 1}{z_t} = \underset{(m+k)\times 1}{u_t} , \qquad (5.15)$$

where $H(L)$ is a nonsingular matrix of polynomials of degree r in L, $z_t = (y_t' , x_t')'$ is a vector of variables and u_t is a vector of normally distributed, serially independent disturbances with mean zero and covariance matrix Σ. Next, Sims tests the lag length (e.g. a four quarter lag against an eight quarter lag) and the stability over time of the parameters. Finally, he tests specific economic hypotheses implying block exogeneity of his model, that is $H_{21}(L) = 0$, where the polynomial matrix $H(L)$ has been partitioned as

$$H(L) = \begin{bmatrix} H_{11}(L) & H_{12}(L) \\ H_{21}(L) & H_{22}(L) \end{bmatrix} . \qquad (5.16)$$

The argumentation for and the implementation of the two approaches briefly described above are quite different in an important number of ways. Hendry and Anderson (1977) and many other authors among whom the present one aim at a parsimonious and theoretically plausible parametrization that is not contradicted by the information in the data, whereas Sims (1980) prefers to work with a loosely parametrized model, arguing that there is not much a priori information available on the parameters.

But the two approaches to modelling systems of simultaneous equations ought to be complementary in their implementation . Lag length, stability of the parameters and block exogeneity have to be tested, when there is doubt about the validity of these assumptions. If the hypothesis of block exogeneity is not rejected, the model for y_t conditionally on x_t as given in (5.12) can be analysed. Otherwise, the joint process for y_t and x_t in (5.15) has to be analysed as a multivariate autoregressive process.

In what follows, we assume that $H_{21}(L) = 0$ and Σ is block diagonal. Next, the investigator can formulate and test overidentifying restrictions on the parameters of his model, perhaps after an investigation into the presence of common factors as has been illustrated by Hendry and Anderson (1977).
There are still some technical problems inherent in the common factor restrictions for vector models. For a thorough discussion about these issues, the reader is referred to e.g. Sargan (1978). Obviously, the question of how to interpret the common factor restrictions arises again. The overidentifying restrictions, which can be similar to those briefly discussed in section 5.1., should preferably be formulated as a sequence of nested hypotheses. The individual significance levels should be adjusted in such a way to assure a given overall probability of an error of type I. The test procedure stops when one null hypothesis in the sequence has to be rejected. Byron (1974) shows how to transform overidentifying structural restrictions into restrictions on the reduced form, which he then tests using a Wald test applied to the whole system. He also provides evidence on the small and large sample properties of the system Wald test.

Dhrymes and al. (1972, p. 299) also state that it might be meaningful to conduct a sequence of nested tests going from general to specific. They propose the Lagrange multiplier test for linear restrictions in a regression model.

The next step in the process of modelling consists in checking the assumptions underlying the most restricted model, for which the restrictions are not rejected by the data. Special attention will be devoted to the residual correlation properties. The work by e.g. Harvey and Phillips (1980) for static and that by Godfrey (1976) for dynamic simultaneous models might be very useful in this context.
Subsequently, the implications of the restricted structural form for the properties of the transfer functions have to be checked.
The set of transfer functions associated with the structural form in (5.12) is obtained through premultiplication of (5.12) by the adjoint matrix of $H_{11}(L)$, $H^*_{11}(L)$,

$$|H_{11}(L)|\, y_t \;=\; - H^*_{11}(L)\, H_{12}(L)\, x_t + H^*_{11}(L)\, u_{1t} \quad , \qquad (5.17)$$

where $|H_{11}(L)|$ is the determinant of $H_{11}(L)$, a scalar polynomial in L of finite degree ($\leq mr$) . As pointed out by Zellner and Palm (1974), the autoregressive polynomials of the transfer functions in (5.17) are identical, provided $H_{11}(L)$ has no special structure such as a diagonal, block diagonal,

triangular or block triangular matrix. Further, the equations in (5.17) form a system of seemingly unrelated dynamic regression equations, each including one endogenous variable, all exogenous variables and a moving average disturbance term. For a more detailed discussion about the properties of the transfer function equations in (5.17), the reader is referred to Zellner and Palm (1974).
As the transfer functions are dynamic regression equations, the lag length and the parameter values for the individual equations in (5.17) can be determined along the lines outlined in section 5.1.

Any incompatibility between the results of the empirical analysis of the individual transfer functions and those derived from the tested structural form is an indication of a misspecification in one or both forms of the model and can be used to reformulate the model.
Examples of how to respecify the model, when an incompatibility is detected, are given by Zellner and Palm (1974, 1975). The transfer functions can also be used to study the dynamic properties of a model. The roots of the characteristic equation associated with (5.12) are obtained by solving $|H_{11}(L^{-1})| = 0$. These roots can be calculated from the estimated autoregressive polynomials of the transfer functions. They determine the time path of the expectations of y_t given the exogenous variables.
Under the additional assumption that the exogenous variables x_t are generated by a multivariate autoregressive model

$$\underset{k\times k}{H_{22}(L)}\ \underset{k\times 1}{x_t} = \underset{k\times 1}{u_{2t}} \quad , \tag{5.18}$$

where u_{2t} is a subvector of u_t in (5.15) and is normally distributed and serially independent with mean zero and covariance matrix Σ_{22} , the final equations for the exogenous variables are obtained through premultiplication of (5.18) by the adjoint matrix of $H_{22}(L)$, $H^*_{22}(L)$,

$$|H_{22}(L)|\ x_t = H^*_{22}(L)\ u_{2t} \quad . \tag{5.19}$$

The determinant of $H_{22}(L)$, $|H_{22}(L)|$, is a scalar polynomial in L . Premultiplication of (5.17) by $|H_{22}(L)|$ and substitution of (5.19) into (5.17) yields

$$\begin{aligned} |H_{22}(L)|\,|H_{11}(L)|\ y_t = &- H^*_{11}(L)\ H_{12}(L)\ H^*_{22}(L)\ u_{2t} + \\ &+ |H_{22}(L)|\ H^*_{11}(L)\ u_{1t} \quad , \end{aligned} \tag{5.20}$$

which is called the set of final equations for the endogenous variables.

The equations in (5.20) form a system of seemingly unrelated ARMA equations for the endogenous variables y_t. Notice that all endogenous variables will usually have the same autoregressive polynomial in the final equations. Our conclusions about the transfer function and the final equation form remain valid if we assume along with Quenouille (1957) or Zellner and Palm (1974) that the disturbances u_{1t} and u_{2t} are generated by vector moving average processes.
As for the transfer functions, any incompatability between the results of the empirical analysis of the individual final equations, e.g. along the lines proposed by BJ (1970), and those for the structural model is an indication of a misspecification of the system of final equations (5.20) and/or of the finally accepted structural form of the model. The role of the empirical analysis of the final equation from for the structural form and for the properties of a simultaneous equation model has been discussed and illustrated by Zellner and Palm (1974).

The analysis of the final equations as a mean for checking out the dynamics of a simultaneous equation model has been pursued by Evans (1978), Prothero and Wallis (1976), Trivedi (1975), Wallis (1977) and Zellner and Palm (1975) among others. Zellner (1979a) discusses some of the statistical problems associated with the SEMTSA approach, that require further research.

The final equations for the exogenous variables in (5.19) can be used to generate future values for the exogenous variables needed in order to forecast future values of the endogenous variables using the structural form. They can also be used to form the expected values of the current exogenous variables in structural models with rational expectations (see e.g. Wallis (1980)).
When the implications of the structural form of the model are in agreement with the results of the empirical analysis of the transfer functions and final equations, the model can be used to predict the post sample period. If post sample data are available, the predictive performance of the structural form can be compared to that of the transfer functions and/or the final equations. If it predicts less well than the transfer functions or the final equations, there are good reasons for believing that the structural model is misspecified.
If all three forms predict badly, the model is either misspecified or it has been subject to a structural change during the sample or the post sample period.

The procedure outlined here ought to be considered as a guideline for modelling systems of dynamic equations. In many occasions, the data will not contain sufficient information to validate or reject all the assumptions underlying a simultaneous equation model, so that the tests will be inconclusive or that the investigator has to rely on non-tested assumptions. Also, as stated at the beginning of this section, an analysis under full information is applicable to small and medium size models only. For instance, Hendry's (1974) model for the expenditures in the United Kingdom contains seven behavioural equations, Sims (1980) analyses vector autoregressive models for the U.S.A. and for West Germany with six endogenous variables. Therefore, in practice, a specification analysis will often have to be pursued under limited information.

In the sequel, we shall discuss some points relating to a single structural equation analysis under limited information.
Consider the following structural equation for a scalar endogenous variable y_t

$$\underset{1\times 1}{y_t} + \underset{1\times(m_1-1)}{\beta'}\ \underset{(m_1-1)\times 1}{y_{1t}} + \underset{1\times k_1}{\gamma'}\ \underset{k_1\times 1}{x_{1t}} = \underset{1\times 1}{\varepsilon_{1t}} , \qquad (5.21)$$

where β and γ are vectors of parameters, y_{1t} and x_{1t} are the vectors of included current endogenous variables and of predetermined variables respectively, ε_{1t} is a normally distributed white noise with variance σ_1^2 . The vector x_{1t} can include lagged values of y_{1t} and other endogenous variables. We assume that x_{1t} and ε_{1t} are independent. Also, we assume that the equation is identified by exclusion restrictions, which imply that the number of excluded predetermined variables $k_0 \geq m_1 - 1$.
However, in order to assure the validity of the assumption of uncorrelated disturbances, a sufficient number of predetermined variables has to be included in (5.21). The assumption of uncorrelated errors has advantages for the identification and estimation of the parameters in (5.21).
Before testing specific hypotheses about the structural parameters in (5.21), the investigator will test for the exogeneity of the m_1-1 elements in y_{1t} . Notice that here the term 'exogenous' has the meaning of 'predetermined' as defined by Engle and al. (1980), that is y_{1t} and u_{1t} are independent. The definitions of weak and strong exogeneity are also given by these authors, who illustrate the relationships among these concepts and their role in econometric modelling by some examples and propose tests of weak exogeneity. We refer the interested reader to their paper.

At present, several exogeneity tests are available (see e.g. Wu (1973, 1974), Farebrother (1976) and Hausman (1978)). Reynolds (1977) developed posterior odds ratios for the independence of stochastic regressors and disturbances.

Sometimes, applied econometricians justify the use of OLS by remarking that these estimates do not differ very much from the estimates obtained by two stage least squares. Most of the existing exogeneity tests are based on a formal comparison of the estimates obtained by a method that is appropriate under the null hypothesis and those by a method that is appropriate under the alternative hypothesis. Hausman (1978) proposed a Wald test. Applied to our problem, the test statistic can be written as

$$T\, \hat{q}'\, \hat{V}\,(\hat{q})^{-1}\hat{q} \quad , \tag{5.22}$$

where T is the sample size, $\hat{q} = \hat{\beta}_1 - \hat{\beta}_0$, with $\hat{\beta}_i$ being estimates of the parameters β , $\hat{V}\,(\hat{q})$ is a consistent estimate of the covariance matrix of $\hat{q}$. If the estimate $\hat{\beta}_0$ is obtained by a method that is consistent, asymptotically efficient and normally distributed under the null hypothesis of the exogeneity (e.g. OLS for equation (5.21)) and the estimate $\hat{\beta}_1$ is consistent and asymptotically normally distributed under the null and the alternative hypothesis (e.g. two stage least squares), the covariance matrix $V\,(\hat{q}) = V\,(\hat{\beta}_1) - V\,(\hat{\beta}_0)$ and the test statistic (5.22) is χ^2-distributed in large samples with $(m_1 - 1)$ degrees of freedom under the null hypothesis. The asymptotic efficiency of $\hat{\beta}_0$ implies that $\hat{\beta}_0$ and $\hat{q}$ are uncorrelated in large samples. Therefore, the test statistic (5.22) is easily obtained, given the estimates $\hat{\beta}_0$ and $\hat{\beta}_1$ and consistent estimates of their covariance matrices.

Upon acceptance of the null hypothesis, equation (5.21) can be analysed as a dynamic regression equation along the lines presented in section 5.1 . Otherwise, the investigator will have to analyse equation (5.21) as a structural equation, using two stage least squares (2SLS), some other instrumental variables method or a maximum likelihood (ML) method to estimate the parameters in the equation.

A likelihood ratio test can be used to test restrictions on the parameters of equation (5.21) given that the restricted and the unrestricted likelihood function have been maximized (under limited or full information).

ML estimates are computationally more expensive. LIML estimates for β and γ can be computed by iterating Zellner's (1962) seemingly unrelated regressions (SUR) estimator, applied to equation (5.21) augmented with the unrestricted reduced form equations for y_{1t} . This has been shown by Pagan (1979) using results by Lahiri and Schmidt (1978).

The hypothesis of exogeneity of y_{1t} is equivalent to the restriction that the covariance matrix of ε_{1t} and the disturbances of the reduced form for y_{1t} is block diagonal. Application of LIML and of two stage least squares require that all the predetermined variables entering the complete model are specified. This is not required when an instrumental variables method (other than 2SLS) is used. For dynamic models, the number of predetermined variables in the system may be large, so that an estimator based on a summary of the information content of the predetermined variables (e.g. the principal components proposed by Kloek and Mennes (1960)) will be used in practice.
The Wald test derived from the asymptotic distribution of the single equation estimates may be preferred for its computational simplicity to a ML test, when we want to test restrictions on the parameters of a single structural equation.
The specification analysis of a single structural equation will in general be conducted along the lines of the analysis of a dynamic regression model, thereby taking explicitly into account the problem of identification and simultaneity.

6. Some concluding remarks

In conclusion, in this paper we have presented the traditional approach to econometric modelling and some procedures proposed in the time series literature. The major part of the paper has been devoted to the SEMTSA approach, which aims at an integration of standard econometric methods and time series techniques and hopefully leads to an optimal blend of both. Though we have several times emphasized the role of economic theory in econometric modelling, little has been said about dynamic economic theory. The fact, that we did not enter more deeply into that body of knowledge, should not be interpreted as evidence against the importance of theory as a basis and guidance for the model specification. Rather, we had to make a choice among the many topics in the economic and econometric literature that are relevant for the econometric model-builder.

Our choice has been oriented towards statistical contributions to and empirical applications of econometric modelling. This is not a coincidence, but can probably be better 'explained' by a comparative advantage on the side of the author. For a valuable and thorough review of the contributions of economic theory to dynamic econometrics, we refer the reader to Nerlove (1972). To his statement on p. 227 that: "Without strong theoretical justification for a particular form of lag distribution, and perhaps even strong prior belief about the quantitative properties of that distribution and the factors on which those properties depend, it is generally impossible to isolate the lag distribution in any very definitive way from the sort of data generally available", we want to add that a theoretically justified dynamic model only lacks a confrontation with 'hard facts', i.e. the empirical validation of the model. Hopefully, we have indicated how this can be achieved.

Several problems, with which an applied econometrician is confronted, have not been discussed. Among them are the problems of the choice of a functional form, the presence of seasonality, errors of measurement, structural changes. Their treatment requires much carefulness from the model-builder.

In addition, a number of questions arise with the formal procedures for econometric modelling in general. The statistical properties of the procedures presented here and those used in practice are only partially known. Anderson (1971) gives some large sample properties of the tests for a uniquely ordered sequence of nested hypotheses. However, as mentioned by Mizon (1977), little is known about the statistical properties of sequential tests, when they are preceded by e.g. checks on the lag length. Fruitful contributions have been made in the field of pretest estimators (see e.g. Judge and Bock (1978)), which have not been discussed here. Some areas of application of the pretesting (e.g. structural estimators) are still relatively unexplored.
Some Monte Carlo results are available for the modelling of specific problems. There is still much room for analytical and Monte Carlo work in this area and it is expected to be very rewarding.

Instead of looking for the statistical properties of the modelling procedure as a whole, one can interpret it as a pursuit of consistency of the accepted model in its different forms with the information available such as a priori information on structural parameters and on multipliers, the conformity of the autocorrelations of the endogenous and exogenous variables and the residuals of the different forms with the properties of the autocorrelation functions implied by the finally accepted model. Many econometricians consider this as a minimum requirement.

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